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Effective Noise Cancellation Technique Using LMS Algorithm in Monte Carlo Simulation

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ABSTRACT:

In this paper we are presenting a method of decreasing this noise and improve the efficiency in Monte Carlo of semiconductor devices. This method exhibits drastically reduced for low signal problems when we compare with standard particle methods like Direct Simulation Monte Carlo methods. The proposed MC can produce efficient visual effects such as depth of field, area lighting, and blur, but it rendered images suffer from objectionable noise at low level sampling rates. The numerical tests shows noise cancellation leads to substantial decrease of the statistical errors and allowing the meaningful results to the raw Monte Carlo estimate. For adaptive noise cancellation we are using LMS algorithm, this method uses a primary noisy signal and the reference input contains a noise correlated with the primary noise. The Extensive Monte Carlo simulation results are presented using MATLAB.

Keywords: Adaptive Noise cancellation, LMS algorithm, Adaptive filter.

I.INTRODUCTION

Adaptive signal processing is an active field of research ever since the pioneering work of windrow. This work is successfully applied to channel equalization and echo cancellation. In this paper we are discuss the adaptive noise cancellation using LMS algorithm in Monte Carlo Simulation. The application of adaptive noise cancellation is a vast application ranging from wireless communication to all telecommunication, audio and biomedical engineering. The signal are known beforehand an optimum filter can be designed according to wiener and Hopf equations. The major problem of this approach is, in the real world the signals input to the filter are not stationary. In such circumstance we must design the adaptive filters are track the changes of signal and noise. In this adaptive filter which uses the filter parameters of a moment ago is to automatically adjust the filter parameters of the present moment of changes to the unknown signal and noise, in order to achieve optimum filtering.

Active Noise Cancellation (ANC) is a method for reducing undesired noise. ANC is achieved by introducing a canceling “anti noise” wave through secondary sources.

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These secondary sources are interconnected through an electronic system using a specific signal processing algorithm for the particular cancellation scheme. Our project is to build a Noise-cancelling headphone by means of active noise control. Essentially, this involves using a microphone, placed near the ear, and electronic circuitry which generates an "antinoise" sound wave with the opposite polarity of the sound wave arriving at the microphone. This results in destructive interference, which cancels out the noise within the enclosed volume of the headphone. This report will demonstrate the approaches that we take on tackling the noise cancellation effects, along with results comparison.

The goal of this work is to develop a framework to harnessthe power of standard, spatially-invariant denoising algorithms to address the problem of noise in Monte Carlorendering. Rather than modifying a specific denoising algorithm for our rendering application as in the AWR method, we want to be able to use any spatially-invariant method for noise reduction.

II.RELATED WORK

The use of Monte Carlo algorithms for rendering was introduced by Cook, in their seminal work that extended standard Whitted ray-tracing to produce a variety of interesting effects, such as depth of fieldand motion blur. Since then, researchers have been exploring a variety of algorithms to reduce the MC noise and produce high-quality images in less time. Several approaches use adaptive sampling to place more samples in the noisy regions and reduce noise. These techniques usually use a local measure of color variance to determine where to place more sample. However, it can often be difficult to tell if the high variance comes from the Monte Carlo noise or from scene detail. Other adaptive algorithms place samples at the vertices of a grid or use a hierarchical data structure that increases resolution in areas that require more samples. These approaches interpolate between samples and have been extended to observe edge boundaries to improve the rendered results. More recently, the multidimensional adaptive sampling algorithm (MDAS) of Hachisuka et al., adaptively samples the space by looking for rapidly changing sample values in all dimensions of integration. Although it can handle general Monte Carlo effects, it suffers from the curse of dimensionality as the number of dimensions increases, so the algorithm performs best when the number of parameters is low.

Solar et al. proposed to leverage sparsity in the Fourier domain to place samples efficiently for scenes with depth of field, while Egan et al addressed the noise of a single Monte Carlo effect with a specialized adaptive sampling scheme in conjunction with asheared reconstruction filter. All of these approaches focuson specific Monte

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Carlo effects and are not general. Finally, Lehtinen et al. exploited the anisotropyof the integrand in MC algorithms by efficiently reusing (orreprojecting) an initial sparse set of samples to get a densersampling. Their method can handle depth of field, motionblur and soft shadow effects. More recently, Lehtinen et al. extended the idea of reprojection to handleglobal illumination.

Finally, Sen and Darabirecently proposed a new filtering approach called random parameter filtering (RPF) where the functional dependency between the scene features and the random parameters are used to guide a cross-bilateralfilter to remove noise but preserve detail. This algorithmcan also handle general Monte Carlo effects, but the simplecross-bilateral filter used in RPF can leave noise behind. Our method works better, as wewill show in the results section.

III. Adaptive Noise Cancellation Using LMS Algorithm

One of the application of adaptive filtering is the problem referred to as noise cancellation. The goal of a noise cancellation is to estimate a signal d(n) from a noise corrupted observation

$X(n)=d(n)+v_1(n)$ (1)

that is recorded by a primary sensor as shown inFig.1. With a noise canceller, the autocorrelation ofthe noise is obtained from a secondary sensor that isplaced within the noise field. Although the noisemeasured by this secondary sensor, v2 (n), will becorrelated with the noise in the primary sensor, thetwo processes will not be equal. There may be anumber of reasons for this, such as differences in thesensor characteristics, differences in the propagationpaths from the noise source to the two sensors, andleakage of the signal d(n) into the measurementsmade by the secondary sensor. Since$V_1(n) \neq V_2(n)$, it is not possible to estimate d(n) by simply subtracting $V_2(n)$ from x(n). Instead, the noise canceller consists of a Wiener filter that is designed to estimate the noise $V_1(n)$ from the signal recived by the second sensor.

This estimate, $\widehat{V}_1(n)$ is then subtracted from the primary signal x(n), to from an estimate of d(n), which is given by

$\hat{d}(n) = x(n) - \widehat{V}_1(n)$ (2)

An example of where such a system may be useful is in air-to-air communications between pilots infighter aircraft or in air-to-ground communications between a pilot and the control tower. Since there is often a large amount of engine and wind noise within the cockpit of the fighter aircraft, communication is often a difficult problem. However, if a secondary microphone is placed within the cockpit of an aircraft, then one may estimate the noise that is transmitted when the pilot speaks into the microphone and subtract this estimate from the transmitted signal, there by increasing the signal-to-noise ratio.If the reference signal$V_2(n)$ is uncorrelated with d(n) then minimizing the mean square error $E\{|e(n)|.^2\}$

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$$E\left\{\left|v_1(n) - \hat{v}_1(n)\right|^2\right\}$$

In other words the output of the adaptive filter is the minimum mean square error estimation of $V_2(n)$.

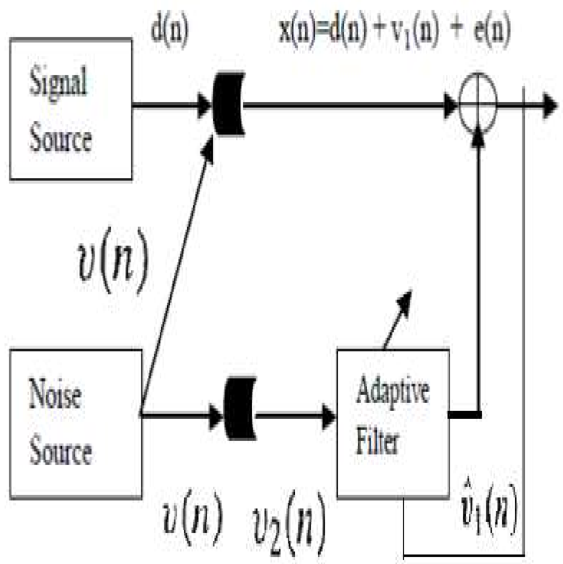

Fig.1. Adaptive noise cancellation using a secondary sensor to measure the additive noise v1 (n).

Basically, if there is no information about d(n) in the reference signal v2(n) ,then the best that the adaptive filter can do to minimize is to remove the part of e(n) that may be estimated from v2(n),which is v1(n). Since the output of the adaptive filter is the minimum mean-square estimate of v1(n), then it follows that e(n) is the minimum mean square estimate of d(n).

IV. Implementation of Noise Cancellation and Monte Carlo Simulation and Results

Let the desired signal be d(n)=sin(0.05πn) and the noise sequence be $V_1(n)$ and $V_2(n)$ as shown in Fig.1. $V_1(n)$ and $V_2(N)$ are assumed to be AR (1) processes that are generated by the following firstorder difference equations

$$V_1(n) = 0.8V_1(n-1) + g(n) \quad (3)$$
$$V_2(n) = -0.6V_1(n-1) + g(n) \quad (4)$$

where g(n) is zero mean, unit variance white noiseand uncorrelated with d(n).The normalized step sizeis taken as 0.008.

For the purpose of presentation of the results in simulation, 1000 samples are considered. Monte Carlo simulation is carried out with 50 number of runs. 1000 samples of desired signal d(n) is generated. For 50 runs, 1000 samples of noise signalg(n) , noise in the primary sensor v1(n), reference signal used by secondary sensor v2(n) and the corrupted signal x(n)(=d(n)+ v1(n)) are generated. For each of the 50 runs, the filter coefficients area djusted such that the mean square error between the filter output i.e., estimate of v1(n) and the corrupted signal x(n) is minimized using LMSalgorithm. For each of the 50 runs, error is calculated by subtracting the estimate of desired signal from d(n). The Root Mean Square (RMS)value of error at each sample is calculated. The RMS value of error at each sample is added to each sample of desired signal and plotted.

FIR Adaptive filters of orders 6, 12 and 24 werefound by solving LMS Algorithm. The

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results areshown in Figures 2(a), 2(b) and 2(c).

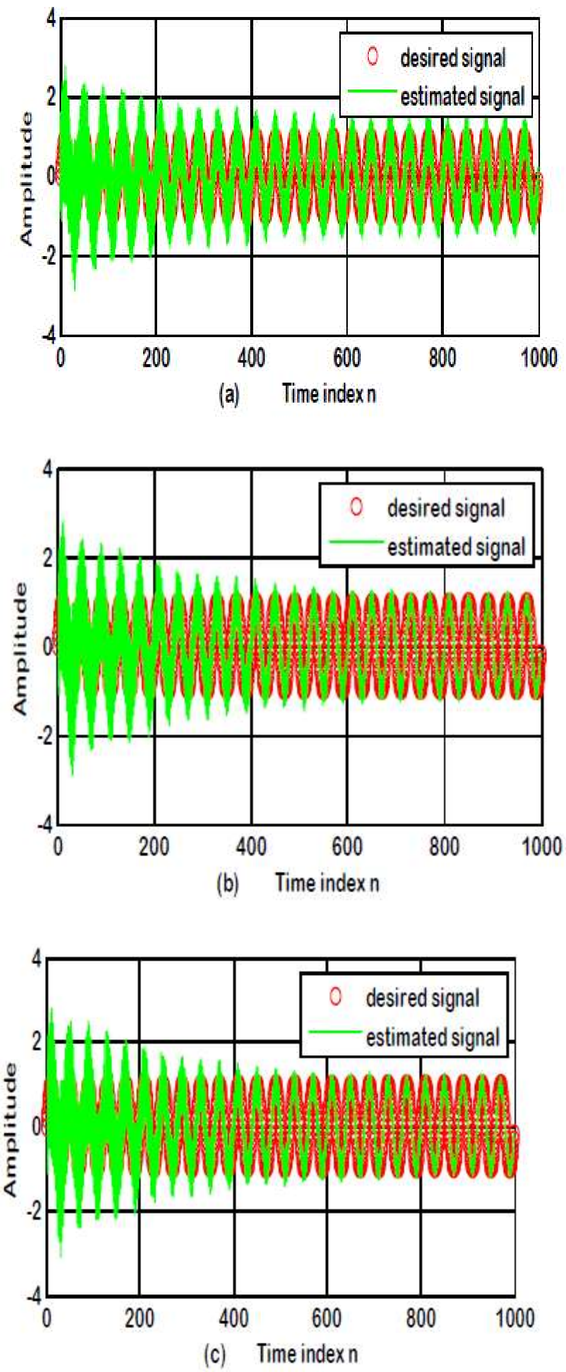

Figure 2. Adaptive Noise Cancellation.

(a) Output of 6th order Adaptive noise canceller,

(b) Output of 12th order Adaptive noise canceller,

(c) Output of 24th order Adaptive noise canceller.

V.CONCLUSION

We have delivered a workable ANC headset for both artificial and real world noise. Our adaptive noise cancelation headset can deal with noise frequency range from 100 to 1000 Hz. We have also incorporate music source. This paper presents to reduce the noise by implementing the adaptive noise cancellation using LMS algorithm in Monte Carlo Simulation and observed results are the satisfactory when the step size parameter μ is selected properly.

VI.REFERENCES:

[1] Monson H. Hayes, “Statistical Digital SignalProcessing and Modeling ”, John Wiley &Sons,Inc.,New York, 1966.

[2] Ying He, Hong He, Li Li , Yi Wu &HongyanPan, “The Applications of Adaptive Filter in NoiseCanceling ” , IEEE International Conference onComputer Science and Software Engineering, 2008.

[3] Paulo S. R. Diniz, “ Adaptive filtering algorithmsand practical implementation ”, Kluwer academicpublishers.

[4] Simon Haykin& Bernard Widrow “ Least MeanSquare Adaptive Filters ”, John Wiley & Sons, Inc., NewJersy, USA 2003.

[5] John R. Glover, Jr., “Adaptive Noise Canceling Applied toSinusoidal

IJMTARC – VOLUME – IV – ISSUE - 14 – June 2016
ISSN: 2320-1363

Interferences", IEEE Trans. ASSP, Vol. ASSP-25, No. 6, pp. 484-491, Dec.1977.

[6] J.R.Zeidler et al., "Adaptive Enhancement of MultipleSinusoids in Uncorrelated Noise", IEEE Trans. ASSP, Vol.ASSP-26, No. 3, pp. 240-254, June 1978.

[7] Ali H. Sayed "Fundamentals of Adaptive Filtering", JohnWiley, 2003.

[8] B. Widrow, et al., "Adaptive Noise Cancelling: Principlesand Applications", Proc. IEEE, vol. 63, pp.1692-1716,Dec. 1975.

[9] S.M. Kuo, D.R. Morgan, Active noise control: a tutorial review, Proc. IEEE 87 (6) (June 1999) 943-975.

[10] S. M. Kuo and D. R. Morgan, Active Noise Control Systems – Algorithms and DSP Implementations. New York: Wiley, 1996.

[11] A. Miguez-Olivares, M. Recuero-Lopez, Development of an Active Noise Controller in the DSP Starter Kit. TI SPRA336. September 1996.

[12] S. Haykin, Adaptive Filter Theory, 2nd ed. Englewood Cliffs, NJ: Prentice-Hall, 1991.

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